# Non-linear 12-lead ECG synthesis from two intracardiac recordings

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# Non-Linear 12-Lead ECG Synthesis from Two Intracardiac Recordings

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## Abstract

*The objective of this study is to facilitate the home follow-up of patients with implantable cardiac devices. To do so, two methods to synthesize 12-lead ECG from two intracardiac EGM, based on dynamic Time Delay artificial Neural Networks are proposed: the direct and the indirect methods. The direct method aims to estimate 12 Transfer Functions (TF) between two EGM and each surface ECG. The indirect method is based on a preliminary orthogonalization phase of ECG and EGM signals, and then the application of the TDNN between these orthogonalized signals. Results, obtained on a dataset issued from 15 patients, suggest that the proposed methods (especially, the indirect method which provides faster results, minimizing data storage) represent an interesting and promising approach to synthesize 12-lead ECG from two EGM signals. Indeed, the correlation coefficients, between the real ECG and the synthesized ECG, lie between 0.76 and 0.99.*

## 1. Introduction

Patients with Implantable Cardiac Devices (ICDs), require regular scheduled hospital visits to perform patient's follow-up and to monitor whether their ICDs is working optimally. Current developments have for objective to propose a remote follow-up of these patients. The cardiac electrical activity acquired from the ICDs, named ElectroGraMs (EGM), show different morphologies, when compared to those of the surface ElectroCardioGram (ECG). Since the physician consider the surface ECG as a reference signal for the analysis of the cardiac activity, we investigate in this study the feasibility of synthesizing the standard 12-lead ECG from only two EGM recordings. The use of these two EGM is justified by the fact that in practice the minimal configuration of ICDs contains always these two EGM leads.

In previous works [1, 2], the 12-lead ECG is synthesized by using linear filtering. However, in a real application, noise and artifacts generated by electrode displacement, changes on the patient's body position or cardio-respiratory interactions may influence the relationships, over time, between the EGM and the ECG. Thus stochastic and non-linear phenomena crop up, and time series dynamics cannot be robustly described using classical linear filtering. We propose in this paper two non-linear methods, namely the direct method and the indirect method, based on a dynamic Time Delay artificial Neural Network (TDNN) [3, 4]. The direct method aims to estimate 12 Transfer Functions (TF) between the two EGM and each ECG lead, and the indirect method is based on: ***i)*** the extraction of a 3-dimensional representation of the surface ECG (or VectorCardioGram, VCG [5]), ***ii)*** the orthogonalization of the two EGM signals, to obtain a VectorGraM [1] (or VGM), by using the Principal Component Analysis (PCA) [6], and ***iii)*** the estimation of three TF between the two VGM and each lead of the obtained VCG.

## 2. Problem formulation and background

### 2.1. Signal Model

The problem that we propose to study can be modeled as follows:

$$\boldsymbol{x}[m] = \mathcal{F}(\boldsymbol{s}[m]) + \boldsymbol{\nu}[m] \quad (1)$$

Where the outputs $\{\boldsymbol{x}[m]\}_{m\in\mathbb{N}}$, representing the surface ECG, are considered as an unspecified non-linear function $\mathcal{F}$ of the inputs $\{\boldsymbol{s}[m]\}_{m\in\mathbb{N}}$, representing the EGM data, plus an additive white noise $\{\boldsymbol{\nu}[m]\}_{m\in\mathbb{N}}$. The problem of the surface ECG signal synthesis can thus be approached by a classical two-step procedure, including a *training step* and a *synthesis step*. The training step aims to identify the function $\mathcal{F}$ ($\mathcal{F}$, is specific to each patient) by using a dataset of $\boldsymbol{x}[m]$ (ECG) and $\boldsymbol{s}[m]$ (EGM) signals, simultaneously acquired in an attended laboratory setting during the implant of the ICD. The synthesis step is devoted to the estimation of surface ECG, $\hat{\boldsymbol{x}}[m]$, by exploiting only the EGM, $\boldsymbol{s}[m]$, and the estimate, $\hat{\mathcal{F}}$ of $\mathcal{F}$. Two different methods, namely the direct method and the indirect method, are proposed to estimate the function $\mathcal{F}$. Nevertheless, before detailing these two methods, let us give a brief description of the 3D cardiac electrical activity and the TDNN architecture, and justify why these tools are used in our approach.

## 2.2. The 3D representation of the cardiac electrical activity

The VCG is an orthogonal lead system that reflects the electrical activity in the three perpendicular directions X, Y, and Z. Although the 12-lead ECG is considered as the reference setup for the analysis of the cardiac electrical activity, the VCG contains useful information for some applications [5, 7]. Indeed, it is well-known that the VCG is superior to the ECG in showing phase differences between electric events in different parts of the heart. In addition, contrary to the standard 12-lead ECG, the analysis based on VCG loops has been found to ***i)*** better compensate the changes in the electrical axis caused by various extracardiac factors [8], such as respiration, body position, electrode positioning, and so forth, ***ii)*** give a compact representation of the cardiac electrical activity, minimizing storage needs, and ***iii)*** provide a solution to the time synchronization problem which arises in cardiac data. These characteristics of the 3D representation of the cardiac electrical activity seem to be useful in our case (see point ***i)*** and ***ii)*** just above). The VCG and the VGM are derived by applying the PCA (see [2] for more details) on the 12-lead ECG and on the two EGM recordings, respectively. For ECG, we just take into account the three largest eigenvalues of the covariance matrix (the PCA is used to reduce and to orthogonalize the ECG data). Regarding the EGM, the two eigenvalues of the covariance matrix are taken into account (in other words, the PCA is not used here to reduce the number of components, but just to orthogonalize the EGM data).

## 2.3. Dynamic Time Delay artificial Neural Network

It is well-known that feed-forward artificial Neural Networks (ANNs) with an input layer, a single hidden layer, and an output layer may be used as universal function approximators, under very general conditions for the activation functions [3,4]. Time Delay ANNs (TDNN) are a particular implementation of feed-forward ANNs, in which delayed versions of the input signals are presented at the input layer of the network. TDNNs have thus an extended capability for time series processing, with respect to feed-forward ANNs, as they include a representation of the $k$ past samples of each input signal.

# 3. Methods

Two steps, namely the training step and the synthesis step, are necessary both for the direct method and the indirect method.

## 3.1. The training step

### 3.1.1. Case of the direct method

Twelve different MISO (Multi-In Single-Out) systems, M1, M2,..., M12, between the two-rows input vector $\boldsymbol{s}[m]$ (EGM) and each row of the output vector $\boldsymbol{x}[m]$ (12-lead ECG) are estimated. For each patient, 12 TDNN are trained by using 20 heartbeats of concurrent ECG and EGM. Each TDNN is defined with an input layer of $N_I = 12 \times k$ samples, a hidden layer of $(N_H)$ neurons with a sigmoid activation function and one linear output neuron.

### 3.1.2. Case of the indirect method

The training step of the indirect method is divided into three sub-steps: ***i)*** the extraction of the 3D cardiac electrical activity of the SECG, ***ii)*** the orthogonalization of the two EGM signals, to obtain a VGM, and ***iii)*** the estimation of the TF between the VGM and the VCG. More precisely, let us consider that $\boldsymbol{x}[m] = [x[m]_1, \cdots, x[m]_N]^{\mathsf{T}}{}_{m=1,\ldots,M}$ and $\boldsymbol{s}[m] = [s[m]_1, \cdots, s[m]_K]^{\mathsf{T}}{}_{m=1,\ldots,M}$ where $N{=}12$ is the number of ECG leads, $K{=}2$ is the number of EGM leads and $M$ is the number of available samples. The estimation of the VCG and the VGM is performed by using PCA [1, 2] so that the following results hold:

$$\begin{aligned} \boldsymbol{z}_{VCG}[m] &= \boldsymbol{W}_{VCG}{}^{\mathsf{T}} \boldsymbol{x}[m] \\ \boldsymbol{z}_{VGM}[m] &= \boldsymbol{W}_{VGM}{}^{\mathsf{T}} \boldsymbol{s}[m] \end{aligned} \tag{2}$$

Where $\boldsymbol{W}_{VCG}$ is an $(12{\times}3)$ matrix and $\boldsymbol{W}_{VGM}$ an $(2{\times}2)$ matrix. Then, three different MISO systems, M1', M2' and M3', between the two-rows input vector $\boldsymbol{z}_{VGM}[m]$ and each row of the output vector $\boldsymbol{z}_{VCG}[m]$, are estimated using a TDNN scheme. Each TDNN is defined with an input layer of $N_I = 3 \times k$ samples, a hidden layer of $(N_H)$ neurons with a sigmoid activation function and one linear output neuron.

Different structures have been tested for the TDNN, by changing $k$ and $N_H$. The best performance (trade-off between the quality of reconstruction and computing time of the training step) is obtained for $k = 4$ samples at the resampled frequency of $128\,Hz$ and $N_H$ of around 50 neurons (the parameters $k$ and $N_H$ are the same for both the direct method and the indirect method). In this paper, the approach proposed by D. MacKay [9] and implemented in the Neural Network Toolbox of Matlab is used to improve the generalization of our procedure and to avoid overfitting.

## 3.2. The synthesis step

Let's suppose that we only observe the EGM of $Q$ successive heartbeats (in our case $Q = 11$). The synthesis step is devoted to the estimation of surface ECG by exploiting

the EGM and different parameters identified in the training step. For the direct method, the 12-lead ECG is obtained directly by using M1, M2,..., M12. Regarding the indirect method, the linear transform $\boldsymbol{W}_{VGM}$ is applied on EGM, which provides us the $(2 \times M')$ VGM matrix (where $M'$ is the number of records of the EGM used in the synthesis step). Then, the $(3 \times M')$ VCG matrix is estimated by using M1', M2' and M3'. Finally, the 12-lead ECG is obtained by multiplying the pseudo-inverse of the linear transform $\boldsymbol{W}_{VCG}$ with the estimated VCG.

# 4. Database and results

## 4.1. Database

A dataset issued from 15 patients (P1 to P15) is used for evaluating the performance of the two proposed methods. The ECG and EGM were simultaneously recorded with a GE Cardiolab station during the implant of ICDs with an initial sampling rate equal to $1000\,Hz$ and then subsampled at $128\,Hz$ and low-pass filtered at $45\,Hz$. Each record of the database is composed of 12 standard surface ECG channels, namely I, II, III, AVR, AVL, AVF, V1, to V6 and two EGM electrodes BIPOA and BIPOVD (which are the electrodes commonly available on dual chamber pacemakers). We also classify the patients into three different types:

- **Type I:** 10 patients (P1 to P10) showing sinus rhythm;
- **Type II:** Three Patients (P11 to P13) presenting some Premature Ventricular Beats (PVB);
- **Type III:** Two patients (P14 and P15) presenting polymorphic beat sequences.

Each patient's file is segmented into two blocks: the first one, containing $L$=20 heartbeats of concurrent ECG and EGM signals, is used in the training step, and the second block, with $Q$=11 beats, is devoted to the synthesis step.

## 4.2. Results

The objective of this section is twofold: ***i)*** to show the behavior of the two proposed methods, namely the direct method and the indirect method, and ***ii)*** to compare the performance provided by each method. Note that, for patients of Type I and Type III, the training dataset and the synthesis dataset contain heartbeats of the same morphologies. In the case of patients of Type II, the PVB heartbeats are not learned (in other words, only the heartbeats of sinus rhythm are considered in the training dataset).

Figures 1 (a) and (a') show examples of real surface ECG (dark line, $\mathrm{I_{Real}}$) and synthesized ECG (gray line, $\mathrm{I_{Rec}}$) for a patient with sinus rhythm (P1) obtained by the direct method and the indirect method, respectively. The synthesis errors of the two methods in this case are practically insignificant. The same behavior is also obtained in the case of patient P15, with polymorphic beat sequences (See figures 1 (c) and (c')). Indeed, all the heartbeats are well estimated, both for the direct method (figure 1 (c)) and the indirect method (figure 1 (c')). Regarding the patient P13 (with PVB), (figures 1 (b) and (b')) exhibit that the two methods provide less reliable estimates for the abnormal beat. However, the results of the two methods could still be useful in a tele-monitoring context, since the synthesized pathological morphologies are very different from sinus beats and the ECG wave durations are preserved. Thus, even if the direct method and the indirect method are not able to exactly reproduce some beat morphologies, they could be used to detect the presence of abnormal ECG beats. In addition, the preservation of the ECG wave durations can be particularly useful to characterize certain pathologies from synthesized beats.

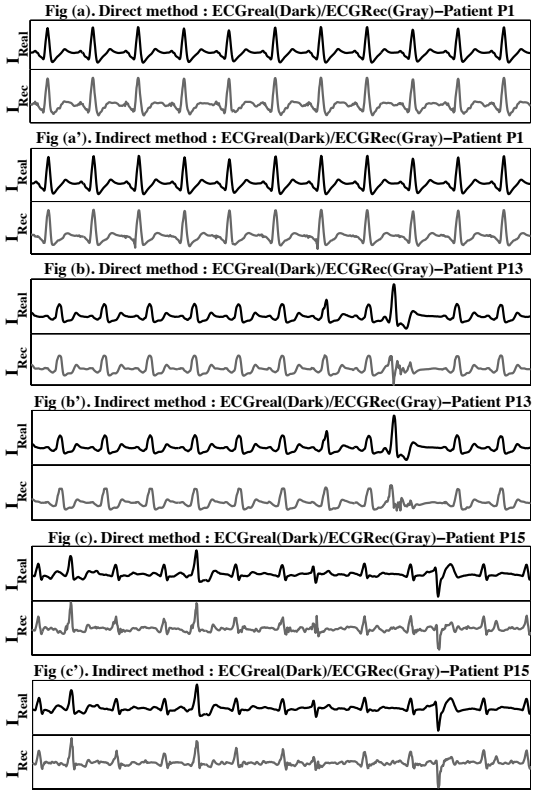


Figure 1. Examples of the synthesized ECG (Real surface ECG: dark line and synthesized ECG: gray line).

In order to compare the quality of the 12-lead ECG synthesis obtained by both methods, we apply them to all the database and we calculate the correlation coefficient between real 12-lead ECG and synthesized 12-lead ECG for each patient and each method. Figures 2 and 3 display the obtained results for each patient and each ECG channel, respectively. We can observe that the performance of the two methods, obtained for each patient and each channel, are equivalent. More precisely, figure 2 shows the very good

performance of the direct method and the indirect method, both for the patients with sinus rhythm (Type I) and with polymorphic beat sequences (Type III). The correlation coefficient between the real ECG and the synthesized ECG is above 0.97 for patients of Type I and lies between [0.86-0.92] for patients P14 and P15. For patients P11, P12 and P13 (Type II) the proposed procedures seem to be less effective in comparison to other patients (correlation coefficient lie between [0.76-0.80]). This result is essentially due to the fact that P11, P12 and P13 present PVB (which are not learned), having different morphologies. It is also interesting to note (see figure 3) that the quality of reconstruction is independent of a particular ECG channel.

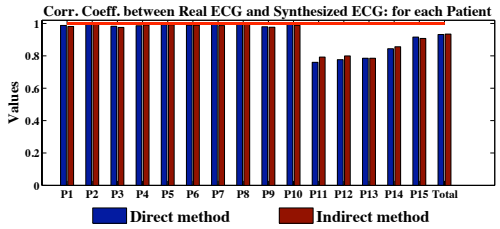


Figure 2. Correlation coefficient between real ECG and synthesized ECG, for each patient, using direct method and indirect method.

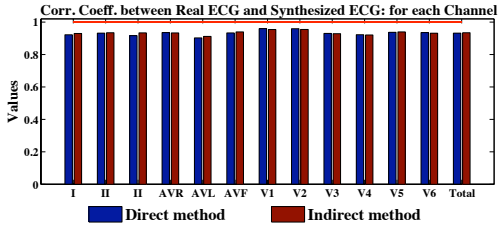


Figure 3. Correlation coefficient between real ECG and synthesized ECG, for each channel, using direct method and indirect method.

## 5. Conclusion

Two methods to synthesize a standard 12-lead ECG from only two EGM, based on a dynamic TDNN, are proposed in this study. A quantitative comparison, conducted on a database issued from 15 patients, shows that the performance of both methods is equivalent. However, as reported in Section 3.1., the direct method requires the learning of 12 transfer functions, whereas the indirect method only requires 3 transfer functions. The simplicity of the indirect method makes it an interesting option for an eventual integration of a TDNN-based reconstruction module, embedded into an ICD. Both methods show an interesting performance for patients on sinus rhythm (Type I) and patients with polymorphic beat sequences (Type III). Regarding the patients of Type II, both methods show limitations on the reproduction of PVB. However, the synthesized abnormal morphologies, obtained from both methods, are very different from sinus beats. In addition, the ECG wave durations of the normal/abnormal beats seem to be preserved, which is useful for a diagnosis purpose (such as the characterization of a bundle branch block). It should be noted that, the performance of our procedures do not depend on the ECG channel to be synthesized. Besides, the proposed solutions are not restricted to only two EGM channels but can be generalized to several EGM channels.

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